2019

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Gera, Ralucca, et al. "An Adaptive Education Approach Using the Learners Social Network." The Fifth International Conference on Human and Social Analytics. 2019.
http://hdl.handle.net/10945/63686

An Adaptive Education Approach Using the Learners' Social Network

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***Abstract*—How can the 21st century education system capitalize on online social networks to support formal education? As education transitions away from the traditional brick-and-mortar style, so does the social network that supports learners. Traditional collegiate education lacks the use of an adaptive system through which students can optimize learning, and educators can promote such learning with the assistance of real-time digital feedback. We develop the means through which the Curated Heuristic Using a Network of Knowledge (CHUNK) learning [6] can provide an adaptive learning framework by designing a dynamic social network of students based on social and academic attributes. Learners use a rating system to determine what educational methods are effective or ineffective in assisting their learning, and the CHUNK Learning system exploits this data to provide other learners more effective methods. We explore the impact that users have on each other when they are considered to be similar based on sharing similar interests. We learn that while different modeling methodology can capture the strength of similarity between users, our experiments show that strongly connected groups have a stronger influence on each other than the weakly connected ones.**

***Index Terms*—Education; Chunk Learning; Adaptive Learning**

I. Introduction and Motivation

Collegiate education is based on traditional lecturer-student interactions where the educator has a preset construct of how the course material should be conveyed to the students, usually in the form of a lecture, for a set amount of time, at frequent intervals, weekly or otherwise. Students are expected to learn the course material via the lectures as well as textbooks and other supplementary methods. Students can pose inquiries to the educator regarding the material to improve their understanding. As a basic educational structure this method works, but can inhibit both those who quickly grasp the subject matter and those who struggle, since they are all exposed to the same information at the same pace.

The newly introduced CHUNK Learning personalized educational system [6] can be found at [1]. Also, references need to be listed as [7], [8] accelerates and deepens learning by introducing targeted short modules for the students. This system allows students to learn in ways that are effective for them, whether it be watching videos, reading the book, reading through slides of the material, working example problems, running code, or a combination of those and other methods. Learning through these activities frees up the lecturing time, allowing the educator to teach at a higher level with deeper classroom discussion; whether that be critical thinking about the learned topics, teaching at an accelerated rate, focusing more on hands-on examples of the learned material, etc. Similar studies and systems looked at web-based and mobile learning CHUNKing of knowledge [2], [13], studying languages [11], [12], math [9], and so on.

Students at the collegiate level and above leave behind generic education that is received during primary and secondary schooling, and begin picking and choosing topics that interest them, and applying to where they see themselves in their future. Naturally, social connections form between students in similar curricula as they go through coursework together, as well as those that live together or participate in extracurricular activities together. These connections grow into a social network of those participating in higher education. From this social network, learning styles can be observed and extended to groups of similar students to help them learn quicker and with greater impact. Adding this social network to CHUNK Learning attempts to best assign content within the learning modules to each person, based on what the social network suggests about their interests, their preferred learning methods, and also the learning methods from their friends. Using this educational aid, students have the ability to learn in a way that makes sense to them and lets them take more away from each education opportunity.

The structure of the paper is as follows. The required definitions and the problem statement are explained in Section II followed by an overview of the related work in Section III. We then introduce the methodology for the recommender system in this environment in Section IV. We present the experimental setup in Section V, followed by the results and interpretation in Section VI. We conclude and present further direction in Section VII.

II. Problem Definitions

As the amount digital information grows, teaching and learning methods must be adapted to enhance education, especially at the collegiate level. Many current methods of education cater to either a lowest common denominator, where the instructor starts at square one for each subject to ensure no student gets left behind, or at a static level in which no consideration is given to the skill levels of the students.

In the first case, the advanced students academically degrade since they are not challenged and waste valuable education time not improving their knowledge and skills. In the second case, the advance students are still not engaged, and those below the level of instruction might constantly struggle with the material, must work disproportionately hard to achieve some level of academic success, and possibly never gain any understanding. For both cases, the failure to appropriately challenge, engage and enlighten students results in sub-par education and a lack of innovation. Meanwhile, a challenging academic atmosphere can lead to just several students graduating with a high level of academic success. In order for the academic environment to improve, education must adapt to all students' levels, capitalizing on their strengths and knowledge, and do so quickly.

CHUNK Learning is a pilot system seeking to enhance education through targeting modules to match the user's learning style and knowledge [6]. The CHUNK Learning system has three main components: a learner profile, CHUNKs, and CHUNKlets. Each of them is tagged with keywords based on the topics to be learned, the teaching method, applications, and so on.

The learner profile captures static information from the learner regarding interests and preferred learning styles. The learner enrolls in a course, and then is presented with the courses' modules, called CHUNKs. Each CHUNK is built around a topic, equivalent to a section in a textbook. The CHUNK content is broken down into smaller education materials, called CHUNKlets. The CHUNKlets capture the breaking down of a topic into short and intense educational materials, allowing the learners to be engaged for a short period of time and practice it before continuing to the next CHUNKlet. The CHUNKlets are categorized into four types: "Why", "What", "Methodology", and "Assessment". For each CHUNK, the CHUNKlets within the same category are interchangeable as they present the same topic from different points of view, allowing for personalized education when the most appropriate CHUNKs are suggested to the learner.

The above structure of CHUNK Learning is complemented with capturing feedback from users. After the completion of a CHUNKlet of a CHUNK, each user can rate how useful and engaging the CHUNKlet was on a scale of one to five. Moreover, users can give thumbs up and thumbs down to the CHUNKlet capturing the relevancy of the learned content. These two measures streamlining the learning process by support an up to date learning environment, as older and less useful content be suggested less.

In the current work, we propose a two step process for recommending CHUNKs and CHUNKlets to each user to support personalized education, based on its current structure. First, relevant CHUNKs and CHUNKlets are determined based on the user's academic requirements and goals. Second, for each relevant CHUNK, the relevant CHUNKlets are rated based on the user's learner profile and the social connections they share with other user's in the system. The goal of this process is to maximize the chances that the user engage with CHUNKlets that are both useful and interesting to him/her. Currently, the recommendation of a CHUNKlet is based on the learner profile's keywords. For this research, we complement the process of personalizing the chosen CHUNKlet for each user by creating and utilizing a social network that ranks relevant CHUNKlets for each user.

The newly proposed rating for each CHUNKlet is generated using the learner's profile and how that information links him/her to similar users, building on the CHUNKlet feedback provided from previous learners in the network. This maximizes the chances learners use methods that work for them. The built in rating system is used to affect the ranking the CHUNKlet receives for other related users in the network, with the strength of that effect being determined by the strength of the individual's social connection with other users. Throughout the paper, "user" and "learner" are used interchangeably.

Our CHUNK Learning approach requires indentifying the relevant connections between the users in order to accurately recommend appropriate new CHUNKlets to users; that is to say it relies on the overlaying social network that emerges between the users of the CHUNK Learning system. This paper seeks to determine a method to generate this social network and apply the CHUNK Learning approach in tandem by having the social network assign and modify the score of each CHUNKlet, to be used for recommendations to other users. The social network's nodes are the individual learner profiles and the edges (weighted and undirected) connect nodes with similar attributes. We extract the attributes from each student profile. Examples of such attributes are the current degree, branch of service, and previous degrees, and extracurricular interests.

III. Related Work

A CHUNK Learning type adaptive algorithm has already been explored by Cleven in his thesis [4], on a set of courses at the Naval Postgraduate School. Cleven investigates how to create an adaptive learning algorithm that links the best suited learning modules to each user, based on user-specific profiles and feedback. Cleven's work focuses on connecting users to the modules that most suit their method of learning, with emphasis on adapting to favor modules that cater to previous user feedback. Cleven's work provides a base example that we extrapolate to create a social network between users. The same feedback mechanism that Cleven uses to create an interpersonal adaptive learning software can be extended to spread feedback across connected users, thus generating an interpersonal adaptability, rather using the CHUNK Learning modules instead of the courses offered at the Naval Postgraduate School. This approach presents a different challenge, as the courses are tagged and capture different information than the modules in CHUNK Learning.

Diffusion of Knowledge is a problem that has been investigated over the last several decades. The basic concept is that certain network layouts are optimally suited for fast and efficient spreading of knowledge. Cowan and Jonard [5] investigate how knowledge spreads throughout three basic network configurations. The first is a regular network, and the second is a random network. The final network layout is the Watts-Strogatz small world network model [10]. Cowan and Jonard show that the more closely connected two nodes are, the higher the rate of knowledge transfer. They find that the layout of a Watts-Strogatz network is most suited to optimal diffusion of knowledge throughout a social network. This concept can be extended to creating interpersonal connections in educational software, facilitating faster learning by users.

A recommender systems that builds on Social Media websites creates a framework for user-to-user connections that complements the content network for a wholistic approach. In the case of Facebook, these connections manifest themselves as friend recommendations, targeted advertising, and preferential displays on a user's feed. Chen and Fong analyze the algorithm that Facebook uses to create similarity functions and trust factors between users [3]. The authors explain that Facebook's similarity function is generated by taking comparison factors between multiple attributes of user profiles, and subsequently assigning a weight to each attribute. For example, the function put more weight on the "interested in" attribute than the "sex" attribute. The attribute weights are determined by the algorithm developers, based on what they believe are more important connecting traits. Trust factors form the second layer of connectivity generation. Facebook trust factors are formed based on a tiered system. Each tier has a discrete trust factor based on the relationship level between users. For instance, family members have a much higher trust factor than users with which one is not Facebook friends [3]. Collaborative Filtering is the notion that a network of user preferences act as an effective way to filter future data. In other words, the network collaborates to determine what data is favored. The Facebook collaborative filter is formed by the combination of the two levels of connection: similarity functions and trust factors, which form a system that determines what content appears on a user's Facebook interface. Similar algorithms could also ahve an impact in creating educational recommendations in an adaptive learning software.

In this paper we introduce a collaborative filtering algorithm that presents CHUNK Learning users with modules preferred by similar users. The introduction of this algorithm into CHUNK Learning facilitate a higher diffusion of knowledge throughout the network of learners. Building on the adaptive learning techniques used by Cleven [4], we present an initial social network framework for the CHUNK Learning system.

IV. Methodology

We create the social network using learner profiles as the nodes, and we use the attributes of those nodes as criteria to create edges. If two nodes have the same attribute, they will be connected by an edge. Attribute selection is limited to a predefined set of options to ensure uniform responses for a given category. This minimizes errors during data entry and ensures rank and designator selections correspond to the selected service. As the network grows, new categories and/or attributes may be added.

For the purposes of this paper, we create a set list of categories and attributes to generate a usable network, as a subset of the CHUNK Learning system's list of attributes. The selected categories have either a drop down list of attributes for single selection or a multiple choice list for attributes which may contain multiple items, such as extracurricular interests and classes. The categories are the following:

1) Rank
2) Service
3) Designator/MOS
4) Masters (Current Curriculum)
5) Major (Previous Degrees)
6) Extracurricular Interests
7) Classes.

Our model focuses on the recommendation of CHUNKlets and assumes CHUNKs have already selected by the user directed for the course he/she is enrolled in, since the CHUNKlets are interchangeable within their category. For the purposes of this research, we limit the model to 11 courses, with each course containing exactly one CHUNK and each CHUNK containing exactly three CHUNKlets. For this reason, the terms "course' and "CHUNK' are interchangeable in our model.

For our analysis, we generate a synthetic social network using MATLAB by creating and connecting fictional users. This allows us to create an environment of users and their initial ratings for each CHUNKlet. Though in reality a user not necessarily complete all CHUNKlets relevant to a particular CHUNK, our model assumes that a user completes and rates all three CHUNKlets relevant to a CHUNK if that user is enrolled in the applicable course. As we introduce new users to the network, we connect them to existing users based on the attributes they select. The MATLAB code also allows us to control the similarity distribution of the users resulting in stronger or weaker connections between the users as similarity is adjusted from high to low.

Using the randomly generated profiles, we create a social network by determining how strongly each user is connected to every other user. First, we weigh how important each category is for determining social connectivity. As an example, current degree may be given a weight of three and past degree may be given a weight of one, indicating connections made using a user's current degree are three times more important than connections made using a user's past degrees. Next, for each category, the category's weight is used to form weighted edges between users if the users share an attribute in that category. Finally, these edges are added together to form the connections in the overall social network, where the weighted edge between each pair of users determines how well-connected they are.

We now explore the effect of the social network on CHUNKlet recommendations. As new users are introduced to the network and connected to existing users, the score of a CHUNKlet is updated for that user and may result in different recommendations. These suggestions for CHUNKlets are based on the highest scored CHUNKlet in that category. Though the method for constructing the edge weights in the social network remains the same, we use three methods for the edge weights to determine CHUNKlet ratings. Let x be a new user, and y, z be existing users in the network.

1) The linear method: the CHUNKlet's rating is proportional to the social edge weights. If the weight of the edge x, y is 5, and the weight of the edge x, z is 10, then user z have twice the impact that user y has on the suggestions presented to x.
2) The exponential method: the impact a user has on CHUNKlet ratings grow exponentially with their social weight.
3) The tier method: in this method, connections between users are split into three tiers according to the social weight connecting them. Highly connected individuals fall into Tier 1, followed by Tier 2, and then Tier 3, as their social weight decreases. All individuals in the same tier have the same impact on CHUNKlet ratings - i.e 6 for the top tier, 3 for the middle, and 1 for the bottom tier.

Each method has potential benefits and drawbacks, which is why we proposed three methods. The tiered approach prevents highly connected users from drowning out less connected users, but could also result in dissimilar users having the same effect as those slightly similar, depending on the bounds of each tier. The exponential method does the opposite, it magnifies the effect highly similar users have on each other. The linear method is the middle ground between tiered and exponential. As more users interact with the CHUNKlets the recommendations become more robust. We present the details in Section V.

V. Experimental Set Up

The goal of our experiments is to determine how adding new users to the CHUNK Learning system affects the CHUNKlets' ratings. In this section, we explain the details of the experiment set up.

A. *Overview*

To focus our approach, we limit ourselves to one specific CHUNKlet of one specific test learner, and observe how the CHUNKlet score for that test learner changes as new users join the network. To minimize the number of variables, the number of original users, the number of new users added, CHUNKlet ratings, and category weighting factors all are held constant between experiments. The original users rate for the observed CHUNKlet is 1, and the new users rate for the observed CHUNKlet is 5. Additionally, we require all users to enrol in just this one single course.

Between experiments, we change how similar the existing and new users are to the test learner. This changes the structure of the social network, which modifies the impact the existing and new users have on the CHUNKlet score to be recommended to the test learner. For each experiment, we use the social network to change the CHUNKlet rating, based on each of the three methods described in Section IV.

B. *Similarity*

To support the goal of our experiment to test how varying the strength of the social network affects a CHUNKlet's rating, we first see how the random profile generator is adjusted to create groups of similar or dissimilar people. The generator uses a parameter called "Similarity' which helps determine the probability of different users sharing attributes. Similarity can take a value greater than or equal to one, and though the value does not have a linear relationship with the probability distribution (a Similarity of 2 does not double the likelihood of creating matching users as compared to a Similarity of 1), higher Similarities increase the likelihood of creating users with matching attributes.

We start the process by creating a vector for each node category, listing attributes for that category. For instance, the vector ["Officer', "Civilian', "Enlisted'] corresponds to the category of Rank. When a new user is created, one of these values is selected randomly for that user's Rank. If Similarity is set to a value of 1 for Rank, then the probability of selecting each value is uniformly distributed, so the user has an equal probability (i.e. $1/3$) of being an Officer, a Civilian, or Enlisted. As similarity is made higher, the probability distribution is shifted to favor attributes in the order listed in the vector. For instance, a Similarity of 10 results in the probability of the new user to be Officer, Civilian, and Enlisted to be approximately $0.69, 0.19$, and 0.12, respectively.

The exact method for choosing a vector's index uses Equation 1, where Similarity variable (S) and Vector Length (L) are parameters. The input value is a random number (r) uniformly distributed between 0 and 1. The output value, $I(r)$, corresponds to the chosen index for that vector. Since the output falls in the interval $[0, L]$, the value is then rounded up to the nearest integer to get the actual index selected. Also, since the vectors do not have an index of 0, then $I(r) = 0$ is replaced with $I(r) = 1$.

$$I(r) = r \cdot L \cdot S^{-(1-r)} \tag{1}$$

Figure 1 shows the output of the Equation 1, where $L = 3$ and $S = 10$.

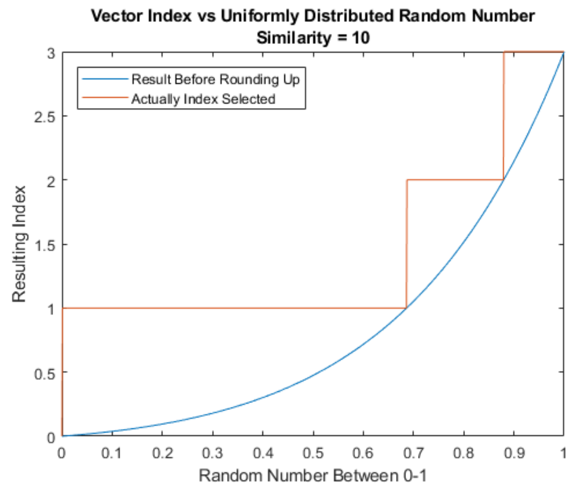

Fig. 1: Chosen Index $I(r)$ vs Random Number r ($L = 3, S = 10$)

Figure 2 shows the probability distribution for selecting a specific index, given $L = 3$and $S = 10$.

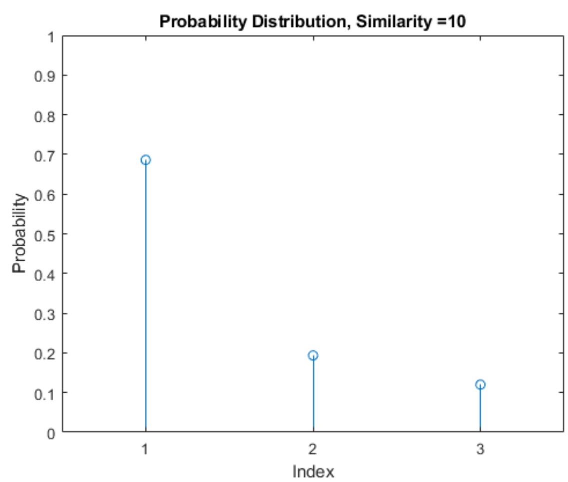

Fig. 2: Index Probability Distribution ($L = 3, S = 10$)

Notice that the probability of selecting index one is much greater than index two or three. Also, the probability of selecting index two is slightly higher than index three. Regardless of the specific values of S and L, lower indices always have a larger probability of being selected than higher indices (except if $S = 1$, in which case the probability is the same for all indices).

C. Experiment Parameters

Each experiment begins with 51 original users that all rate the observed CHUNKlets with a rating of 1. One of the original 51 users is the test learner, and his attributes remain constant between experiments. Note that since we are observing the CHUNKlet's score for the test learner, his ranking does not actual affect the CHUNKlet score (since there are no loops in the social network). The other 50 original users have their similarity to the test learner varied between experiments.

Next, 50 new users are added, one at a time, which all rate the observed CHUNKlet with a rating of 5. The 50 new users have their similarity to the test learner varied between experiments. The observed CHUNKlet score is recorded for each new user added, so a trend of *CHUNKlet score* versus *number of new users* added can be determined.

The available categories for each user profile are Rank, Service, Designator, Current Degree, Previous Degrees, Extra-curricular Interests, and Enrolled Classes. The weight for each category is assigned as $2, 2, 2, 3, 3, 2$, and 1, respectively, and they remain constant between experiments.

The users are selected as *test learner* and *other users* (that come in groups of Similar, Dissimilar, or Realistic people), and are defined as follows:

- The test learner: which remains constant between experiments, always chooses the first (most likely) attribute for each category. For instance, since the Rank vector is [“Officer’,“Civilian’,“Enlisted’], the test learner is always an officer.
- Similar people use a Similarity value of 9000 for every category (see Section V-B for more details); therefore, there is a high probability each member of this group is similar to other members of the group as well as the test learner.
- Dissimilar people use a Similarity value of 1. This creates an equal chance of choosing any attribute for each category, so the chance that each person in this group is similar to the test learner is completely random.
- Realistic people attempt to better simulate the learner population at the Naval Postgraduate School. Their Rank category is given a Similarity of 100, which gives each person in the group a 0.81 probability of being an officer. Their Service category is given a similarity of 5, which gives each military person in the group a 0.42 probability of being in the Navy. All other categories for this group have a Similarity of 1. The specific probabilities of choosing a index depends on the vector length for that category, Table I shows the probability distribution for a vector length of f5 and Similarities of $5, 100$, and 9000.

TABLE I: INDEX PROBABILITY FOR VARIOUS SIMILARITIES

	Index 1	Index 2	Index 3	Index 4	Index 5
S=5	0.4723	0.1999	0.1363	0.1071	0.0844
S=100	0.7243	0.1177	0.0659	0.0525	0.0396
S=9000	0.8449	0.0661	0.0377	0.0281	0.0232

The first experiment looks at an extreme case where the 50 original people are dissimilar, and the 50 new people are similar. The second experiment uses 50 realistic people as the original group, and 50 similar people are added one at the time. Finally, the third experiment uses 50 realistic people as the original group, and 50 dissimilar are added one at the time. Table II, below, summarizes the experiment groupings.

TABLE II: EXPERIMENT GROUP TYPES

	Original People	New People
Exp 1	Dissimilar	Similar
Exp 2	Realistic	Similar
Exp 3	Realistic	Dissimilar

VI. Results and Analysis

We run each of the experiments described in Section V one time, and record the CHUNKlet score for each new person added. For each experiment, the random number generator is reset, so if nothing else changes, the people generated are identical.

The *CHUNKlet score* versus *number of people added* is graphed in Figures 3-5 for each experiment. Each graph contains four lines. The purple line is used to mark the reference value of 3, the score the CHUNKlet would receive if the test user received no input from the social network. The blue, yellow, and red lines correspond to the linear, exponential, and tiered methods of using social weighting, respectively. For more details on these methods, see Section IV. It should be noted that the exponential and tiered methods are very dependent on the equations and parameters used for those methods. These experiments show only one way the tiered and exponential methods could be established.

We now dedicate a subsection to each experiment established by Table II. Each subsection presents the *CHUNKlet score* versus *new people added*, and be followed by a brief analysis of the results. Note that since the original people always rate the CHUNKlet as 1, the CHUNKlet score always starts as 1, with zero new people added. Also, since the new people always rate the CHUNKlet as 5, the CHUNKlet score always increases as new people are added.

A. Experiment 1: 50 Dissimilar & 50 Similar

As expected, due to the high similarity of the new group, the CHUNKlet score quickly becomes closer to 5 than it is to 1. Due to the high social network values in the Similar group, the exponential method has a significantly greater effect on the CHUNKlet score than the other two methods. The exponential method only requires about eight new people to return the CHUNKlet score to the baseline of 3. The linear and tiered methods require between 15 and 20 people, which is still low considering the original group contains 50 people. The final CHUNKlet score for the exponential method is about 4.25, with the linear and tiered methods having a score just under 4.

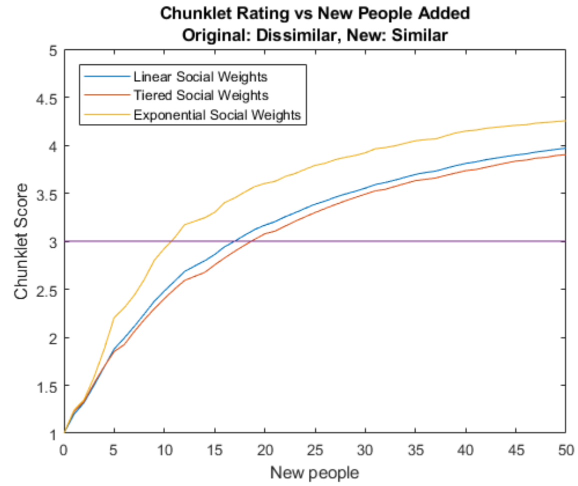

Fig. 3: Experiment 1 Results

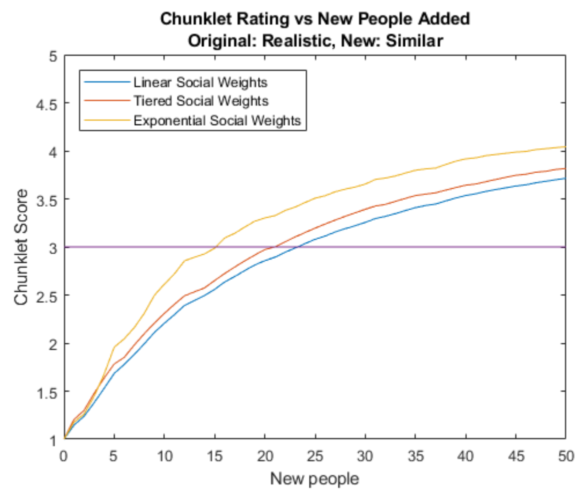

Fig. 4: Experiment 2 Results

B. Experiment 2: 50 Realistic & 50 Similar

As opposed to the first experiment, the original group of people in this experiment are better connected socially. Due to this, the one ratings of the original 50 people carry more weight, so the CHUNKlet score rises slower and reaches a smaller final value. Still, the new people are still better connected than the original people, so the final score is still well above the baseline of 3. The exponential method is still dominant due to the large values in the new group's social network. Of note, the tiered method has a higher final value than the linear method, which is reversed from the first experiment. Since the 50 new people are exactly the same in both experiments, we believe the difference is due to the change in social network for the 50 original people. Therefore, for the parameters used to establish this tiered system, the tiered method appears to carry more weight when the group is Dissimilar than it does when the group is Realistic.

C. Experiment 3: 50 Realistic & 50 Dissimilar

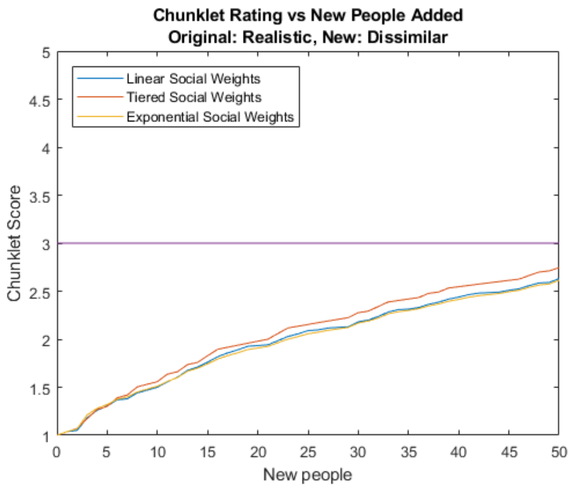

Fig. 5: Experiment 3 Results

The final experiment has a new group which is less connected than the original group. As expected, the CHUNKlet score does not reach the baseline of 3. With no Similar group, the values in the social network are much lower. This appears to cause the exponential method to have a nearly identical effect as the linear method. The tiered method now has the highest final value. This is once again mostly likely due to the relatively smaller effect this tiered system has when dealing with the Realistic populations.

VII. Conclusions and Further Directions

Current teaching methods do not customize the experience to the individual in order to maximize educational gains. The CHUNK Learning system brings attention to this deficiency by assigning material to users that is both relevant to their learning goals as well as compatible with their interests and learning styles. Our method uses the attributes of each CHUNK user profile to establish a social network which helps direct people towards learning materials (CHUNKlets) that are most compatible to their profile.

Our experiments examined how changing the similarity between people in a social network affected CHUNKlet scores. Additionally, three methods for utilizing the social network to affect CHUNKlet scores were examined: linear, exponential, and tiered. No matter which method was used, the experiments always showed that strongly connected groups had a greater effect on CHUNKlets scores than weakly connected groups. This is a validation of our concept, since people that share more of your interests have a greater effect on your recommended learning material.

Another result of the experiments is that the methods used to implement the social network has a variable degree of effect depending on the strength of the connections in the social network. For example, the exponential method appears to have a dominant effect for highly connected social networks, but as the network acquires dissimilar users, the exponential method becomes nearly indistinguishable from the linear method. However, the exact way in which the different methods interact with different social networks is dependent on the equations and parameters that define those methods.

To better understand how a social network affects CHUNKlet scores, an extensive survey is required so that real user data can be collected and used. Only then can the effects of the different social network weighting techniques be analyzed and adjusted. Additionally, user feedback is required to determine if the recommended CHUNKlets are actually well tailored to the individuals based on their social connections. This user feedback can be used to adjust the parameters of the social network, such as the available categories and attributes as well as the weighting factor for each category.

Acknowledgments

The authors would like to thank the DoD for partially funding this work.

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